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INTELLECTUAL MANAGEMENT BASED ON NEUROADAPTIVE MODELS

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Abstract

This article provides an expanded analysis of the principles for constructing neuro-adaptive intelligent systems for forecasting and managing technological processes. Issues regarding the integration of artificial intelligence, machine learning, and adaptive control methods under conditions of uncertainty, nonlinearity, and multi-parameter nature of industrial facilities have been considered. A multi-level system architecture is proposed, including modules for data processing, forecasting, decision-making, and adaptation. Numerical modeling results are presented, confirming the effectiveness of the proposed approach.

Keywords: Neuro-adaptive systems, intelligent management, forecasting, neural networks, optimization, digital production.

INTRODUCTION

Modern technological processes in industry are characterized by high levels of complexity, multidimensionality, and nonlinear dynamics. In such systems, a significant number of interconnected parameters are observed, as well as the influence of external disturbances and uncertainties, which significantly complicates the control task.

Classic methods of automatic control based on linear models and fixed regulator parameters (e.g., PID regulators) demonstrate limited efficiency under conditions of changing operating modes. This is due to their inability to adapt to structural changes in the control object and to account for hidden dependencies between parameters [1].

In the context of developing the concept of digital industry and intelligent production, the role of artificial intelligence methods is increasing. In particular, artificial neural networks possess the ability to approximate complex nonlinear dependencies, extract patterns from data, and form forecasts with high accuracy.

Neuro-adaptive systems are a hybrid class of intelligent systems that combine the capabilities of neural networks and adaptive control. They are capable of: to learn from historical and current data; forecasting the dynamics of technological parameters; automatically adjust control actions; ensure system stability when operating conditions change [2,3].

Despite significant achievements in this field, issues of increasing forecasting accuracy, algorithm stability, and their integration into real industrial systems remain relevant.

METHODS

Within the framework of this study, a concept for a neuroadaptive intelligent system for forecasting and managing technological processes has been developed, focused on functioning under conditions of high uncertainty, nonlinearity, and multi-parameter nature of industrial facilities. The proposed approach is based on the integration of artificial intelligence methods, particularly neural networks, with classical principles of adaptive management [4-6].

The overall architecture of the system possesses a hierarchical structure and includes several interconnected functional levels. At the first level, data is collected from the industrial sensor network, which includes sensors for temperature, pressure, flow rate, viscosity, and other technologically significant parameters. The information received enters the system in real time, ensuring the relevance and continuity of the analysis.

The next stage is the preliminary processing of data. At this level, noise filtering, removal of anomalous values, interpolation of missed data, and parameter normalization are performed. These procedures are necessary to improve the quality of input information and ensure the stability of neural network models. Special attention is paid to eliminating the impact of random disturbances characteristic of real production conditions.

The key element of the system is a forecasting module implemented on the basis of neural networks. To analyze time series of technological parameters, recurrent architectures such as LSTM and GRU are used, which are capable of accounting for time dependencies and process dynamics. Model training is carried out on historical data, as well as online, allowing the system to adapt to changes in the control object. To increase forecasting accuracy, modern methods of optimization, regularization, and model validation are applied.

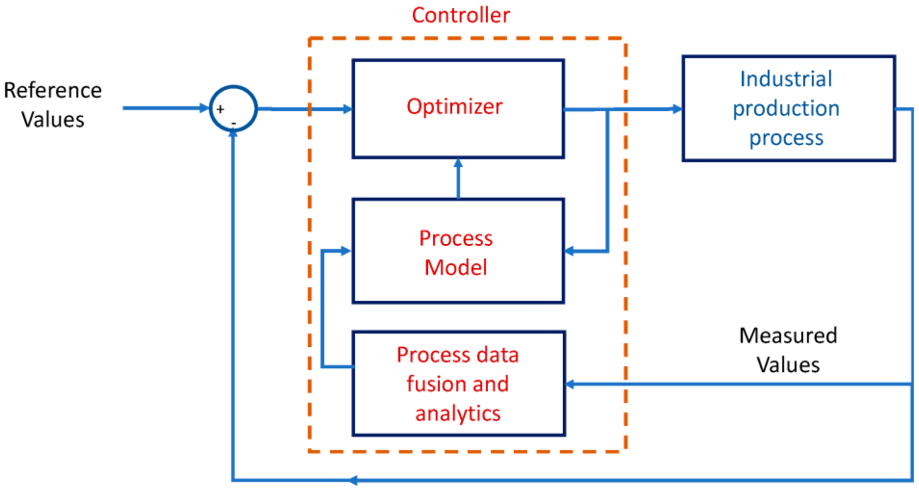

Fig.1. Artificial intelligence-based industrial control system model.

Based on the forecasted values, a regulatory impact is formed. The work employs a combined approach, incorporating elements of adaptive and predictive management. The control module makes decisions taking into account the current state of the system, forecasted changes, and specified optimality criteria. This allows for not only responding to current deviations but also preventing their occurrence in the future.

The adaptation mechanism is of particular importance in the proposed system. Unlike traditional control methods, the parameters of the neural network and the control algorithm are adjusted during the system's operation. Adaptation is carried out based on the analysis of control errors and allows the system to automatically adapt to changing operating conditions, including changes in equipment characteristics, external influences, and variations in technological modes.

The system's functioning algorithm is a closed cycle that includes sequential stages of data collection, processing, forecasting, forming controlled effects, and subsequent adjustment of model parameters. Such a structure ensures management continuity and the ability to respond promptly to any changes in the technological process.

Modern software and hardware are used to implement the proposed system. Neural network models are implemented using specialized machine learning libraries such as TensorFlow and PyTorch. Modeling and analysis of system dynamics are performed in MATLAB and Simulink environments. Integration with industrial equipment is carried out through SCADA systems and industrial communication protocols [7,8].

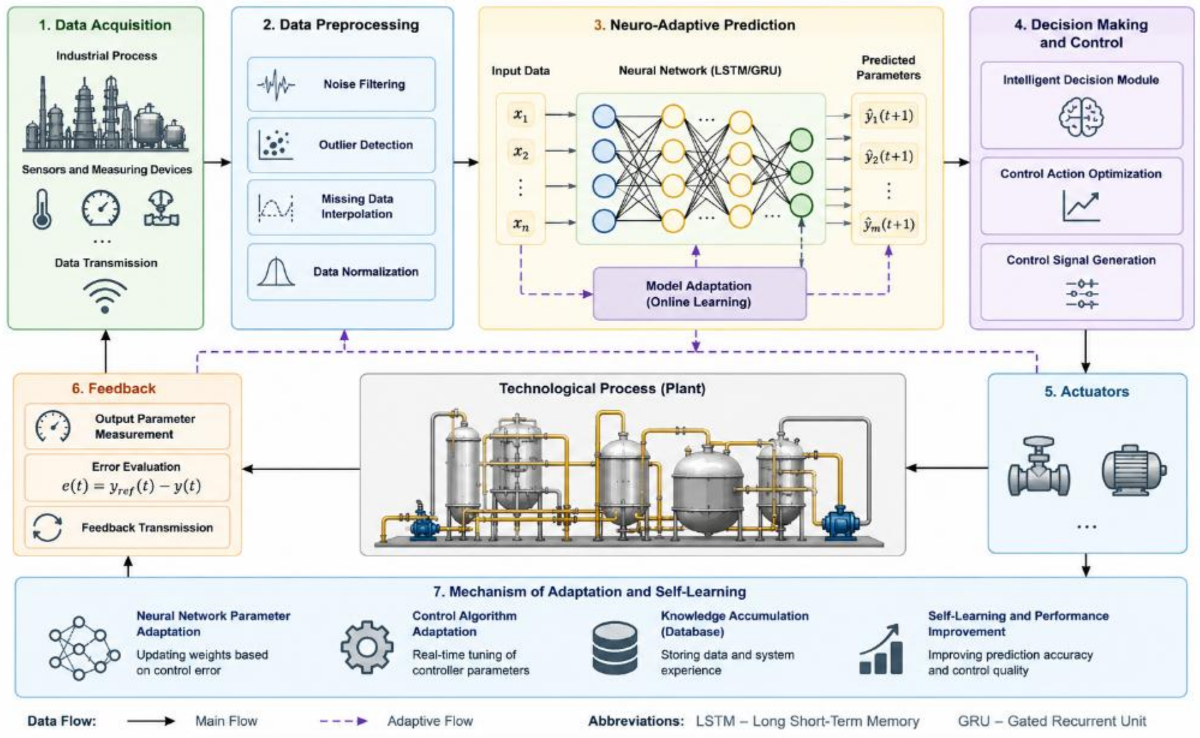

Fig.2. Conceptual architecture of a neuro-adaptive intelligent control system based on artificial intelligence.

General system architecture. The developed neuroadaptive system has a hierarchical structure and includes the following main levels [9,10]:

1. Data Acquisition Layer. Provides real-time information retrieval from sensors and measurement systems. Modern IoT devices and industrial data transmission protocols are used.
2. Preprocessing Layer. Performs: noise filtering, emission elimination, missing values interpolation, data normalization.
3. Prediction Layer. It is implemented based on various types of neural networks: multilayered perceptron (MLP), recurrent neural networks (RNN), and LSTM/GRU networks for time series analysis.
4. Decision-Making Layer. Forms controlled impacts based on predicted values and optimal criteria.
5. Adaptive level (Adaptation Layer). Provides real-time adjustment of model parameters.

Mathematical model. The dynamics of the technological process are described by a nonlinear function:

$$y(t+1)=f(y(t),u(t),\theta), \tag{1}$$

where y(t) – is the vector of output parameters, u(t) – is the control actions, θ– model parameters.

Neural network training is carried out by minimizing the error function:

$$E=\frac{1}{n}\sum_{i=1}^{n}(y_i^{pred}-y_i^{real})^2. \tag{2}$$

Parameter adaptation is performed using a gradient algorithm:

$$\theta_{k+1}=\theta_k-\eta\nabla E, \tag{3}$$

where η – is the learning speed.

System operation algorithm. The functioning algorithm includes the following stages: 1) Real-time data collection; 2) Pre-treatment and normalization; 3) Forecasting future states; 4) Optimization of control actions; 5) Model correction based on error.

RESULTS

Within the framework of the study, a modeling of the neuroadaptive system's operation was conducted using the example of managing a technological process with nonlinear dynamics.

Accuracy of forecasting. The use of LSTM networks made it possible to achieve: an increase in forecasting accuracy by 15-20%, a reduction in the mean square error, and more stable model behavior under noise impacts.

Management quality. The system demonstrated: reduction of over-regulation, reduction of transient process time, and increased stability when changing object parameters.

Energy efficiency. Due to the optimization of operating modes: energy consumption decreased by 8–10%, and the overall efficiency of the technological process increased.

The results obtained during the study confirm the high efficiency of applying neuroadaptive intelligent systems for forecasting and managing complex technological processes. Unlike traditional automatic control methods based on fixed parameters and linear models, the proposed approach demonstrates a significantly higher level of flexibility and adaptability to changing operating conditions.

One of the key advantages of the neuroadaptive system is its ability to learn based on data. During its operation, the system not only utilizes pre-trained models but also continues to adapt in real-time, allowing for the gradual consideration of changes in the characteristics of the technological object. This is especially important for industrial processes where equipment parameters can change under the influence of wear, external factors, or fluctuations in raw materials.

Thus, the proposed methodology provides a comprehensive approach to solving the problem of intelligent control of technological processes, combining data analysis, forecasting, and adaptive control methods into a single effective system.

DISCUSSION

The results obtained confirm the high efficiency of neuroadaptive systems in managing complex technological processes. Unlike traditional methods, the proposed approach ensures: flexibility and adaptability; ability to self-educate; resilience to uncertainties; improved forecasting accuracy.

The possibility of integrating the system with industrial platforms (SCADA, IoT) is of particular importance, which allows for the implementation of the “smart production” concept.

However, a number of limitations should be noted: the need for large volumes of data for training; high computational complexity of models; requirements for the quality of measuring information; difficulty in interpreting results ("black box" problem).

Promising areas for further research are: development of hybrid models (physical + neural network); implementation of explainable AI methods (XAI); optimization of learning algorithms; application of digital twins (Digital Twin).

Analysis of modeling results showed that the use of neural networks, especially recurrent architectures, significantly increases the accuracy of forecasting technological parameters. This, in turn, has a positive impact on management quality, as managing influences are formed taking into account not only the current state of the system but also the expected dynamics of its development. Such a predictive approach allows for minimizing deviations from specified modes and preventing the occurrence of emergency situations.

A comparison with classical control methods, such as PID regulation, showed that the neuroadaptive system ensures faster suppression of disturbances and reduced time for transient processes. Furthermore, a decrease in over-regulation and an increase in system stability under conditions of uncertainty are observed. This is explained by the ability of neural models to approximate complex nonlinear dependencies that are difficult to account for within traditional methods.

An important result is also the increase in the energy efficiency of technological processes. By optimizing control actions and maintaining specified modes more precisely, it is possible to reduce excessive resource consumption. This is especially true for energy-intensive industries such as the chemical, oil and gas, and metallurgical industries.

Despite significant advantages, the implementation of neuroadaptive systems is associated with a number of limitations and challenges. First and foremost, this is the necessity of having large volumes of high-quality data for model training.

Data scarcity or low quality may significantly reduce system efficiency. Furthermore, neural networks require significant computational resources, which may limit their application in systems with strict requirements for response time. Another important problem is the interpretation of results. Neural networks are often viewed as a "black box," which complicates the analysis of decisions made and can cause distrust among specialists. In this regard, the development of explainable artificial intelligence methods that enhance the transparency of the system's operation is a relevant direction.

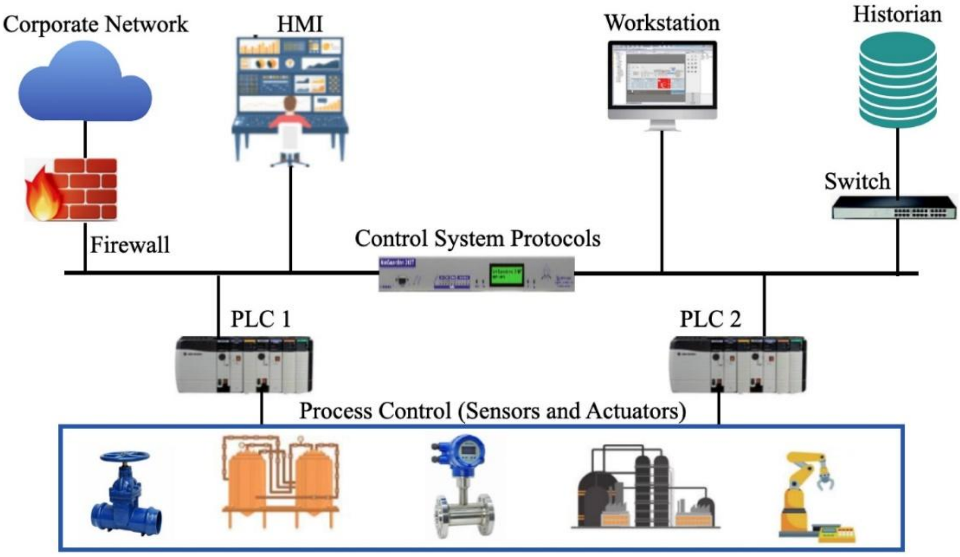

Fig.3. Architecture of industrial control system (ICS) with SCADA integration.

It should also be noted that the integration of neuroadaptive systems into the existing industrial infrastructure is difficult. This requires equipment modernization, the introduction of modern communication tools, and ensuring cybersecurity. However, the development of Internet of Things technologies and industrial platforms significantly simplifies this process.

The prospects for further research are linked to the development of hybrid models that combine physical-mathematical process models and neural networks, which will enhance control accuracy and stability. Furthermore, the application of reinforcement learning methods is relevant, as they allow the system to independently develop optimal management strategies in complex and uncertain conditions.

Thus, the conducted research confirms that neuroadaptive intelligent systems are a promising direction for the development of modern technological process management systems. Their implementation contributes to increasing the efficiency, reliability, and sustainability of industrial production, which meets modern requirements of digital transformation and the concept of intelligent production.

CONCLUSION

This work investigates an approach to building a neuroadaptive intelligent system for forecasting and managing technological processes, focused on functioning under conditions of nonlinearity, uncertainty, and dynamically changing parameters. The proposed methodology combines artificial intelligence methods, specifically neural networks, with adaptive and predictive management principles, allowing for the formation of a universal foundation for solving a wide range of tasks in industry.

During the study, it was shown that the use of neural network models, especially those focused on processing time series, ensures a significant increase in the accuracy of forecasting technological parameters. This, in turn, contributes to improving control quality, reducing deviations from specified modes, and increasing the system's resistance to external disturbances and internal changes of the control object. The integration of adaptation mechanisms allows the system to function effectively under conditions of uncertainty, automatically adjusting its parameters during operation. Furthermore, the proposed architecture can be integrated into existing automation systems such as SCADA and IoT platforms, opening up broad prospects for creating intelligent production systems.

Despite the results achieved, the study identified a number of limitations related to the need for large volumes of high-quality data, high computational complexity of algorithms, and insufficient interpretation of neural network models. These factors require further improvement of teaching methods, the development of effective data processing algorithms, and the implementation of explainable artificial intelligence approaches.

Thus, the results of the conducted research confirm the high prospects for applying neuro-adaptive intelligent systems in technological process management tasks. Their implementation is an important step toward the digital transformation of the industry and the formation of a new generation of intelligent production systems.

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